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Review Article

Revealing the benefits of entropy weights method for multi-objective optimization in machining operations: A critical review

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ABSTRACT

Machining operation optimization improves the quality of the product, reduces cost, enhances overall efficiency by reducing human error, and enables consistent and efficient operation. It is a vital decision-making process and achieves the best solution within constraints. It reduces reliance on machine-tool technicians and handbooks to identify cutting parameters, as a lack of awareness of the optimal combination of machining parameters leads to several machining inefficiencies. Subsequently, the optimization of the machining process is more useful for units of production, particularly machining units. In multi-objective optimization (MOO) problems, weights of importance are assigned, mostly identical. But, nowadays, the weights assignment techniques have received a lot of consideration from the professionals and researchers in MOO problems. Various techniques are developed to assign weights of significance to responses in MOO. The Entropy weights method (EWM) continues to work pleasingly across diverse machining operations to allocate objective weights. In this paper, a literature review is conducted to classify the articles on EWM applications in machining operations. The categorization proposal for the EWM reviews included 65 academic articles from different journals, books, and conferences since the year 2009. The EWM applications were separated into 18 categories of conventional and non-conventional machining operations. The implementation procedure of EWM is presented with an example along with method development. Scholarly articles in the EWM applications are further inferred based on (1) implementation of EWM in different machining operations, (2) MOO methods used with entropy weights in machining operations, (3) application of entropy weights by citation index and publication year, and (4) entropy weights applications in other fields. The review paper provided constructive

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insight into the EWM applications and ended with suggestions for further research in machining and different areas.

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List of abbreviations

AE	Angular error
AECM	Active energy consumed by the machine
AHP	Analytic hierarchy process
ANN	Artificial neural network
ANOVA	Analysis of variance
APCE	Active power consumed by the machine
C	Cost
CentryE	Circularity at entry error
CexitE	Circularity at exit error
CF	Cutting force
CNC	Computer numerical Control
CR	Cutting rate
CT	Cutting temperature
D	Density
Db	Exit diameter
Df	Delamination factor
Div	Degrees of divergence
Dt	Entrance diameter
DT	Decision template
ECSM	Electrochemical spark machining
EDAS	Evaluation based on distance from average solution
EDDG	Electric discharge diamond grinding
EDG	Electric discharge drilling
EDM	Electrical discharge machining
EE	Energy efficiency
En	Entropy
EW	Entropy weights
EWM	Entropy weights method
EWR	Electrode wear rate
FEM	Finite element method
FT	Fracture toughness
FW	Flank wear
Fzl	Fuzzy logic
G	Gap and radial overcut
GA	Genetic algorithm
GEP	Gene expression programming
GPE	Global percentage error
GRA	Grey relational analysis
GRD	Grey relational degree or grade
H	Hardness
i	1, 2, ..., a no. of experiments (n)
j	1,2, ..., no. of responses (m)]
Krfd	Kerf deviation
Krft	Kerf thickness
Krfw	Kerf width
LBC	Laser beam cutting
LBM	Laser beam machining
LBPD	Laser beam percussion drilling
LTT	Laser trepan turning
n	Number of responses
Maxi	Maximum
MCDM	Multiple criteria decision making
MH	Micro hardness
Mini	Minimum
MOO	Multi objective optimization
MOORA	Multi objective optimization Method by ratio analysis
MRR	Metal removal rate
n	Number of experiments
NCIRentry	Normalized circularity at entry
NCIRexit	Normalized circularity at exit
NDM	Normalized decision matrix
NHT	Normalized hole taper
NSGA-II	Non-dominated sorting genetic algorithm-II
OEC	Overall evaluation criteria
PC	Power consumption
PCA	Principal component analysis
PF	Power factor
PFc	Primary force
Pr	Probability of the response
Prod.	Productivity
PSO	Particle swarm optimization
RA	Regression analysis
Ra	Surface roughness
Rd	Roundness
REWR	Relative electrode wear rate
Rmax	Maximum roughness depth
Rq	Root mean square
RSb	Surface residual stress of machined bottom surface
RSM	Response surface methodology
RSs	Surface residual stress of machined surface
Rt	Maximum height of the profile
Rz	Average maximum height of the profile
SAW	Simple additive weighting
SCE	Specific cutting energy
SCI	Science citation index
SE	Shannon entropy
SEC	Specific energy consumption
SF	Secondary force
SOW-W	Subjective and objective weighted method
SRb	Surface roughness of machined bottom surface
TA	Taper angle
TC	High thermal conductivity
ThF	Thrust force
TL	Tool life

TOPSIS	Technique for order preference by similarity to ideal solution	VIKOR	Vlsekriterijumskaoptimizacija I kompromisnoresenje
TS	Thermal stability	VMD	Variational mode decomposition
TW	Tool wear	WASPAS	Weighted aggregated sum product assessment
TWR	Tool wear rate	WEDM	Wire electrical discharge machining
USM	Ultrasonic machining	WWR	Wheel wear rate
		YM	Young modulus

1. Introduction

It has long been recognized that cutting conditions should be chosen to maximize the economics of machining operations, as measured by efficiency, the overall manufacturing cost per part, or some other acceptable criteria. But, for an optimum range of cutting conditions and tools, production companies have long relied on the skill and expertise of shop-floor machine-tool technicians. The manufacturing units are still using handbooks to pick cutting parameters and tools at the process level. The most detrimental consequence of such an unscientific method is lowered efficiency attributable to the suboptimal application of machining capacities [1]. The optimization in machining operations is one of the vital decision-making processes. It achieves the best design or solution out of the available solutions within constraints. Machining process optimization results in more effective operation, removing unnecessary steps, and automating the overall process to save time, reduce mistakes and eliminate repetitive work. The improved productivity by process optimization can be of significant help, particularly for continuous operations, the ones that take place daily. It's always good for workers to function more effectively, assisted by the right software resources. A lack of clarity of the optimal combination of machining parameters causes many inefficiencies in machining operations [2]. Consequently, the machining operation optimization becomes more useful for manufacturing, especially machining units. As optimization leads to more flexibility, to use the right software solutions with more accurate information and optimal combination of machining parameters also enhances production and quality with additional profits [3].

The multi-objective optimization (MOO) techniques utilize response weights in their process of converting multiple responses into single response value (composite score or performance index). These weights to responses participate uniquely in obtaining the composite index of responses. It's very important for the decision-maker that he must have an understanding of the true meaning of weights and its computation. So, the involvement of weights of importance in MOO problems is a crucial phase of the entire optimization process. The weights to responses in MOO can be assigned in different ways, such as equal, subjective, objective, and combinations of objective and subjective weights. It is a significant step in optimization because concluding results mainly depend upon allocated weights, but generally, weights are assigned equally [3]. The subjective weight calculation involves the judgment of the decision-maker (engineer, manager, or any other person participates in the research or have experience of the process or operation). The subjective weights obtained replicate the personal opinion of the decision-maker and influence the concluding results of the optimization problem. The subjective weights calculation methods include such as Ranking weighting [4], Direct weighting method [5], Allocation of points [6], Simple attribute rating technique, SMARTER [7], Swing [8], Trade-off [9], Pairwise comparison [10], AHP [11], the Least square method [12], Eigenvector method [13], Delphi method [14], Pattern method and Consistent matrix analysis. The computation of objective weights involves mathematical models or algorithms based upon the investigation of preliminary data, and there is no involvement of the decision-maker by neglecting skewed opinion information. The objective weights calculation techniques comprise for example Entropy method [3,15], Vertical and Horizontal method [16], TOPSIS [17], Variant coefficient [18], Multi-objective optimization method, Multiple correlation coefficient [19], Principal component analysis method [20] and so on [21]. The combinations of weights calculations involve both ways objective and subjective. These methods include Multiplication synthesis and Additive synthesis etc. The weighting methods are also classified based on internal and external types [22].

In MOO decision-making problems, weights of significance are assigned, mostly alike. Nevertheless, the weights assignment methods have been established by professionals and researchers. Various techniques were developed to assign weights of significance to responses in MOO. This review aims to provide a collective information of Entropy weights methodology applied to different machining operations which compute the objective weights. Further, it enables calculating the relative weights of responses in a simple, uncomplicated way and is an immensely successful practice for evaluating indicators. Indeed, we can recognize that the EWM allows a quantitative assessment of the efficiency of machining responses. The EWM also can detect the weak impact of some unusual machining attributes and makes the outcome of the assessment gradually precise and rational. The EWM methodology can be used for various fields and thoroughly collection of EWM applications in machining operations can be helpful for the practitioners and researchers. The remaining paper is categorized into five parts. Section 2 presents a concise outline and the execution of EWM. Section 3 explains the structure of articles collected for the study. Section 4 illustrates detailed scrutiny of 18 different machining operations with entropy weights. Section 5 dispenses the EWM

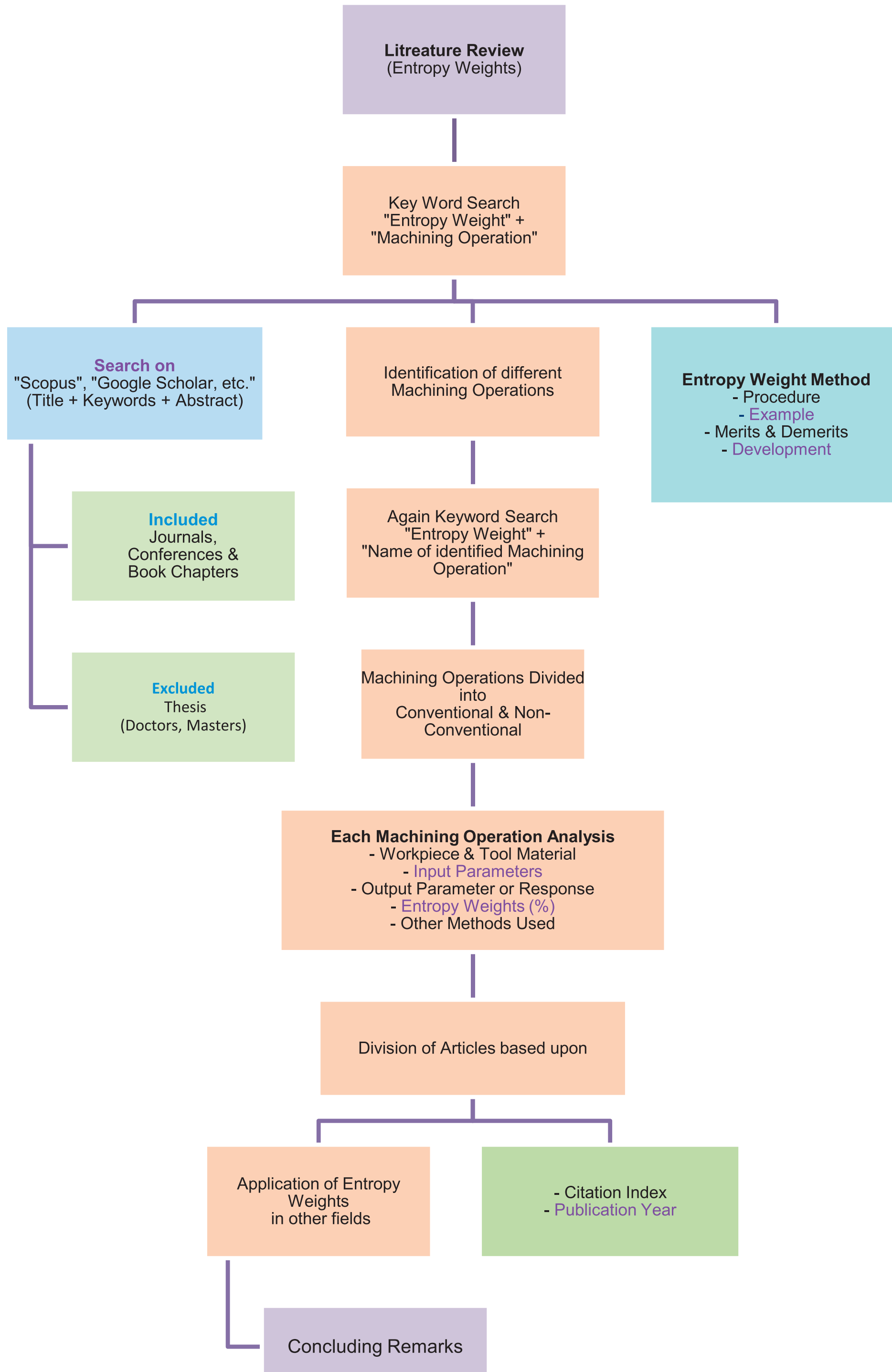

Fig. 1 – Entropy weights method: review methodology.

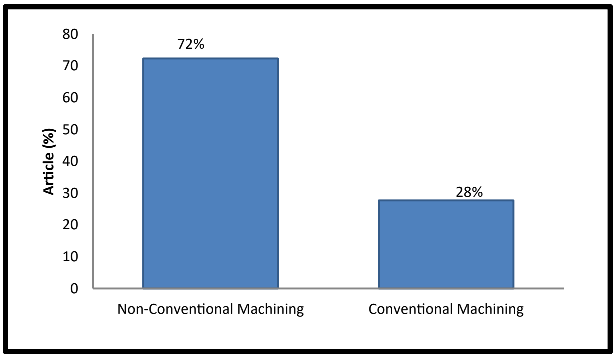

Fig. 2 – Entropy weights applications in machining.

papers into four new groups. Lastly, Section 6 briefly explains the concluding statement.

2. Entropy weights method (EWM)

Shannon and Weaver proposed EWM in 1947 [23], and Zeleny has emphasized further developments in 1982. The EWM is utilized to establish the objective weights of the attributes/responses. The probability theory is utilized to compute uncertain information (Entropy). It determines the importance of every response, not including any thoughtfulness of the preference of the decider (engineer or manager). The EWM works on the principle that superior weight indicator information is more constructive than the lower indicator information. This method includes first deciding objectives (decision matrix) and then calculations of the normalized decision matrix, probability of the attribute/response to take place, the entropy value of attribute/response, degrees of divergence (average information contained) by each response and after that entropy weight [3,24]. The following steps are taken by this method to compute objective weights.

Step 1 Objective

Alternatives/experiments are worked out with suitable evaluation criteria/responses allied with it (e.g., design of experiments).

Step 2 Decision Matrix

The decision template is given away in Eq. (1). Every row of decision template or matrix is allotted to one experiment and all columns to one response (e.g., MRR, Ra, tool life, etc.). Accordingly, the e_{ij} of the decision template 'DT' [e_{ij}; i = 1, 2, ..., a no. of experiments (n), j = 1,2, ..., no. of responses (m)] are contributions for decision template or matrix.

$$DT = \begin{bmatrix} q_{11} & q_{12} & -- & q_{1j} & -- & q_{1m} \\ q_{21} & q_{22} & -- & q_{2j} & -- & q_{2m} \\ -- & -- & -- & -- & -- & -- \\ q_{i1} & q_{i2} & -- & q_{ij} & -- & q_{im} \\ -- & -- & -- & -- & -- & -- \\ q_{n1} & q_{n2} & -- & q_{nj} & -- & q_{nm} \end{bmatrix} \quad (1)$$

Step 3 Normalization

The linear normalization technique is utilized to make the experimental data of 'DT' dimensionless due to several units of the responses. Eq. (2) is used for beneficial response, e.g., MRR and Eq. (3) for a non-beneficial reaction, e.g., Ra and it is noticeable that normalized decision matrix $NDM_{ij} \in [0,1]$.

$$NDM_{ij} = \frac{q_{ij}}{Maxq_{ij}} (\text{Beneficial}) \quad (2)$$

$$NDM_{ij} = \frac{Minq_{ij}}{q_{ij}} (\text{Non}-\text{beneficial}) \quad (3)$$

Step 4 Probability and Entropy

The probability of the response (Pr_{ij}) to happen, be computed by Eq. (4) and Eq. (5) is utilized to attain the Entropy (En_j) of the jth response.

$$Pr_{ij} = \frac{NDM_{ij}}{\sum_{i=1}^{n} NDM_{ij}} \quad (4)$$

$$En_j = -Y \sum_{i=1}^{n} Pr_{ij} \log_e (Pr_{ij}) \quad (5)$$

where $Y = \frac{1}{\log_e(n)}$ is a stable expression, n belongs to no. of experiments and value of En_j lies between zero and one.

Step 5 Divergence and Entropy Weights

Eq. (6) is utilized to compute the degrees of divergence (Div_j), and Eq. (7) obtains the entropy weight (Ew) of the jth response.

$$Div_j = |1 - En_j| \quad (6)$$

$$Ew_j = \frac{Div_j}{\sum_{j=1}^{m} Div_j} \quad (7)$$

2.1. *Example of entropy weight method*

The MOO problem from [25] is taken to understand the steps involved in computing the entropy weights. This problem is

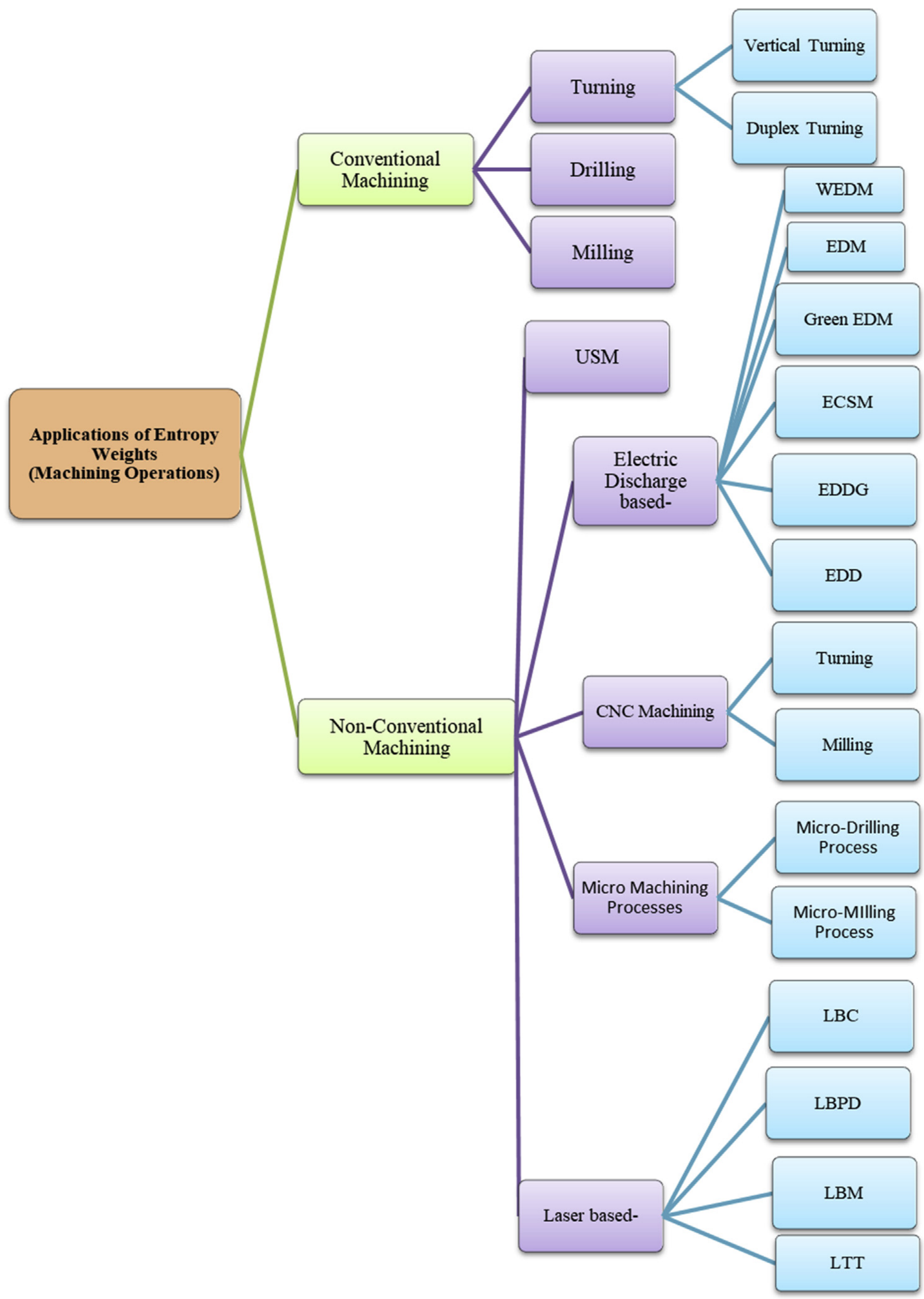

Fig. 3 – Application of entropy weights identified machining operations.

solved in the excel sheet (MS office-2007), and the detailed steps involved are illustrated below as per the methodology above;

Step 1 Objectives

The objectives, as per step 1, are considered. The MOO includes the maximization of MRR and minimization of Ra and machining time [25].

Step 2 Decision Matrix

The decision matrix, according to step 2, is shown in Table 1, and it consists of nine experiments and three responses viz. material removal rate (MRR), surface roughness (Ra), and time as per Eq. (1).

The linear normalization technique is utilized to make the experimental data of Table 1 dimensionless due to several units of the responses. Eq. (2) is used for a beneficial response, and Table 1 shows the maximum and minimum values of the responses MRR, Ra, and time. In this case, the maximum amount of MRR is 471. Each experiment value of the response (MRR) is divided by 471, e.g., experiment no. 1; $\frac{188}{471} = 0.3992$, similarly, other values are calculated and shown in Table 2.

Eq. (3) is utilized for a non-beneficial response, e.g., Ra and time. The minimum value of Ra is 0.502, and this value divided by each experiment value of the response Ra, e.g., experiment no. 1, $\frac{0.502}{1.144} = 0.4388$, and for time $\frac{25}{38} = 0.6579$. The normalized decision matrix is shown in Table 2.

Step 4 Probability and Entropy

Probability of the criterion (Pr_{ij}) computed as per Eq. (4). The sum of all the normalized values from experiment numbers 1 to 9 are shown in Table 2 at the bottom row. The probability of the MRR, Ra, and time is computed by dividing the value of every experiment by the sum of the responses, e.g., MRR of experiment number 1,

$$Pr_{ij} = \frac{0.3992}{0.3992+0.6667+1+0.569+0.8896+0.6391+0.7558+0.5669+0.9066} = \frac{0.3992}{6.3928} = 0.0624.$$

Similarly, other values of the probability are calculated and are shown in Table 3.

The Entropy of each response MRR, Ra, and time is computed by Eq. (5). The term Y in Eq. (5) is calculated as $Y = \frac{1}{\log_e(n)}$. In the present case, the value of n is nine, i.e., the number of experiments.

$$Y = \frac{1}{\log_e(9)} = \frac{1}{2.1972} = 0.4551.$$

The calculations of the term $Pr_{ij}\log_e(Pr_{ij})$ of Eq. (5) are shown in Table 4, e.g., experiment number 1 of the response MRR;

$$0.0624 \times log_e(0.0624) = 0.0624 \times (-2.7736) = -0.1732.$$

The calculations of the term $\sum_{i=1}^{n} Pr_{ij}\log_e(Pr_{ij})$ of Eq. (5) are shown in Table 4 at serial no. I, e.g., experiment number 1 of the response MRR;

$$(-0.1732)+(-0.2357)+(-0.2902)+(-0.2153)+(-0.2744)+(-0.2302)+(-0.2524)+(-0.2148)+(-0.277) = -2.1634,$$

And the Entropy En_j calculations are shown in Table 4 at serial number III.

The degree of divergence is computed by Eq. (6) as shown in Table 4 at serial number IV, e.g., experiment number 1 of the response:

$$MRR; 1 - 0.9846 = 0.0154$$

$$Ra;\ 1 - 0.9771 = 0.0229$$

$$Time;\ 1 - 0.99486 = 0.0052$$

The sum of divergence is shown in Table 4 at serial number V, e.g.

$$0.0154 + 0.0229 + 0.0052 = 0.0424$$

Eq. (7) is utilized to obtain entropy weights as shown in Table 4 at serial number VI,e.g.,

$$MRR; \frac{0.0154}{0.0424} = 0.3551$$

$$Ra;\ \frac{0.0229}{0.0424} = 0.5273$$

$$Time; \frac{0.0052}{0.0424} = 0.1187$$

The entropy weights in terms of percentage are shown in Table 4 at serial number VII.

2.2. *Benefits and limitations of EWM*

Followings are the advantages of the EWM approach:

- The EWM calculates the relative weights of responses in a simple, uncomplicated, and impartial way.
- The EWM strategy for calculating weight is a hugely successful technique for assessing indicators.
- This approach is established as adequately consistent in identifying together contrast intensity and divergence of responses in addition to figuring their weights suitably.
- The EWM proposes if the accessible information is sufficient or not, and if not, then supplementary information should be required. As a result, EWM fetches the model, the modeller, and the decision-maker nearer.
- The EWM allows a quantitative appraisal of effectiveness and advantage/cost responses. The EWM for computing of weight considers sufficiently the data of qualities of all the observing segments provided to adjust the relationship among various assessing objects. The EWM debilitates the weak impact of some unusual attributes and makes the outcome of assessment progressively precise and sensible.
- The conventional EWM spotlights on the separation amid information to decide quality weights. If a response can separate the information more adequately, it is specified a superior weight.
- The EWM strategy delivers more different coefficient esteems for responses. It's suitable for the Entropy strategy to handle the fundamental disagreement between the responses in decision-making [26].

Apart from the various benefits, the downsides of the EWM are as follows:

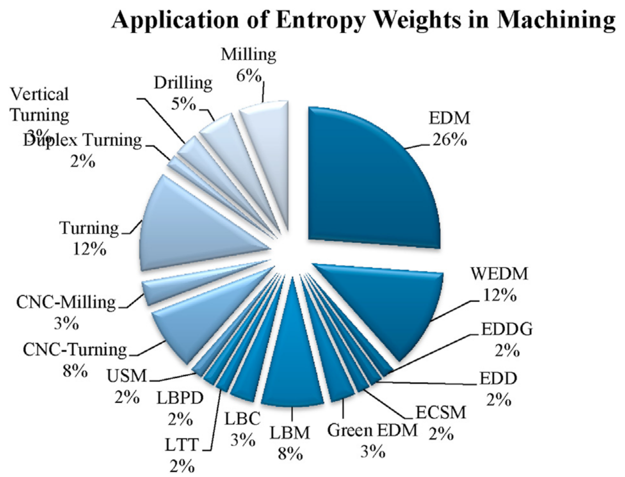

Fig. 4 – Application of entropy weights in machining operations.

- The EWM's possible drawback connected to appropriate problem sizing, e.g., the decision matrix encloses an adequately massive set of alternatives [27].
- The EWM computed weights lacking specialist verdict, and it only considers entropy values.
- The EWM does not provide any participation in the designer's preferences.
- The weights of responses computed by the standard deviation technique are more inclusive and persuasive than EWM. Because, this method judges not only the quantity of information every response holds, however, as well the impact of every response on decision-making. At the same time, the EWM considers no description of the reciprocated associations amongst responses [28].
- The effectiveness of EWM in decision making reported that the discretion of the EWM is problematic as it pays no attention to rank discrimination [29].

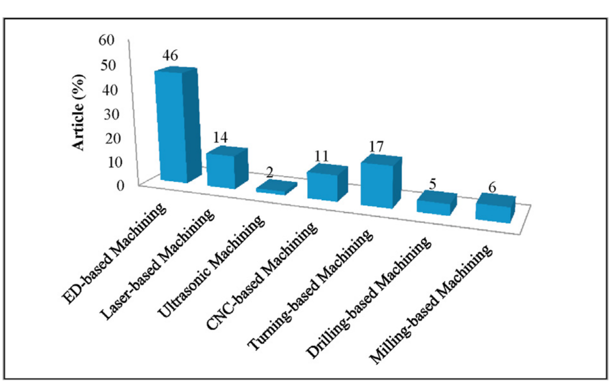

Fig. 5 – Article contribution: different groups of machining operations.

2.3. *Evolution of entropy method*

The EWM developed over time and is implemented in different areas of engineering and other fields. EWM contribute a vital role in calculating objective weights of significance in MOO response of different machining process. Table 5 presents thorough progress of the Entropy technique application in diverse fields.

2.4. *Cross-entropy technique*

The cross-entropy technique is utilized for the significance of optimization and sampling is a Monte Carlo technique. It applies to equally combinatorial and continuous problems, with either a static or noisy objective. Table 6 presents a cross-entropy technique applied to different machining operations. Table 6 also includes minimum cross-entropy, normalized cross-entropy, fuzzy entropy control applications to various machining operations.

3. Structures for literature review

The structure of the review of the literature is shown in Fig. 1. The articles associated with doctoral, master theses, and without publication are not considered in the present review. Different 18 machining operations were identified which have an application of EWM. Then, "entropy weights" and the name of different machining operations were again searched one by one on Scopus, Google Scholar, Mendeley, Web of Science, Springer, and Science Direct as a keyword. The primary data for EWM reviews collected from Google Scholar articles published since 2009. The collected papers in this review were analysed and divided into conventional and non-conventional machining operations.

For each machining operation, the input parameters, workpiece material, tool material, output parameters, or responses with entropy weights assigned, and MOO methods used are presented for individual machining operation. The collected articles are also classified as other categories such as EWM in different machining operations, different MOO methods used with entropy weights in machining operations, application of entropy weights by citation index and publication year, EWM publication journals, first authors' nationality, and a few articles of entropy weight applications in other fields. The EWM review on machining presents a precious foundation for research and academic fraternity. The literature review of EWM applications in machining operations commenced identifying the articles in journals, conferences, and book chapters that offer the most precious knowledge to an academic fraternity. The papers searched extensively on Scopus, Google Scholar, Mendeley, Web of Science, Springer, and Science Direct.

4. Applications of entropy weights in machining operations

This section presents a comprehensive review of the 65 academic and research articles divided into conventional and

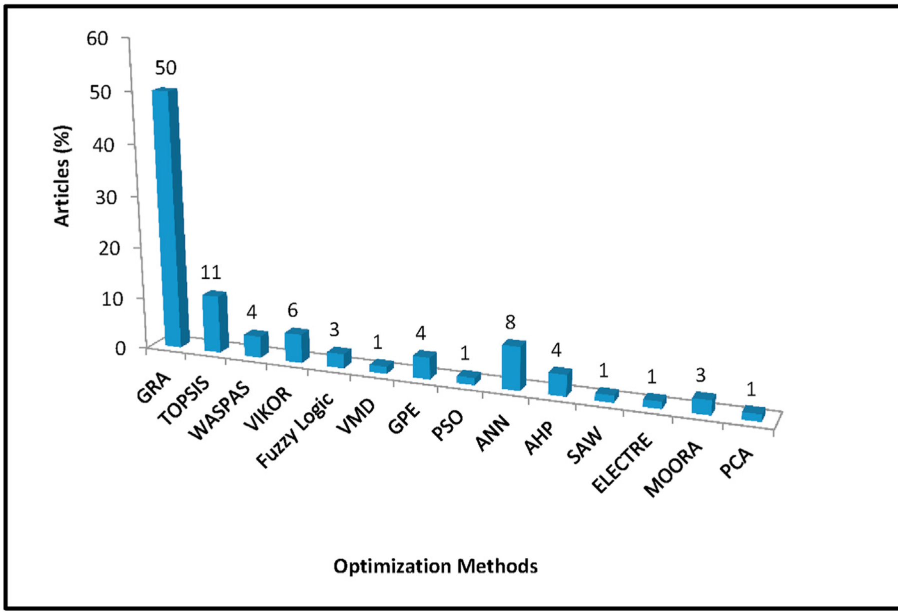

Fig. 6 – Different optimization methods used.

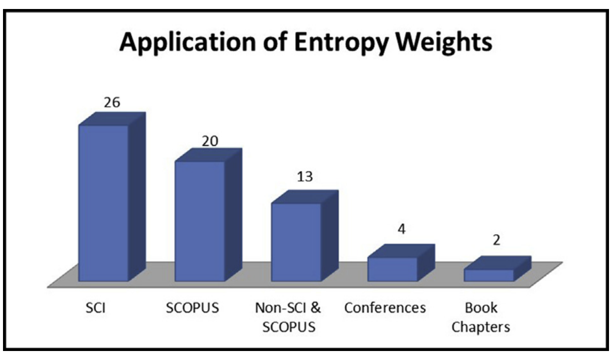

Fig. 7 – Application of entropy weights by publication type.

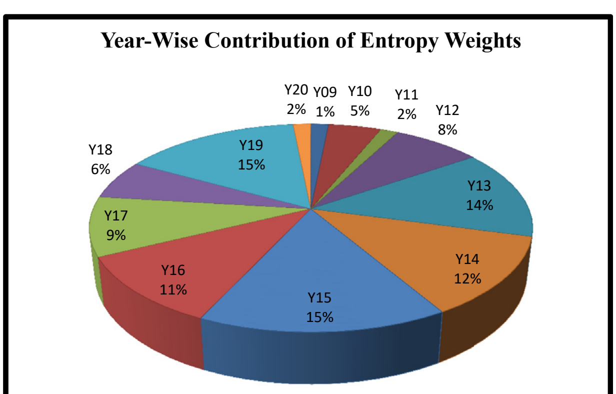

Fig. 8 – Year-wise contribution of Entropy method in machining.

non-conventional machining operations, as shown in Fig. 2. Further, the different machining operations identified from the collected literature having the use of entropy weights is shown in Fig. 3. The review of papers in terms of percentage application of entropy weights is shown in Fig. 4. The analysis of papers briefly revealed in each section as per machining operation, and each machining operation is summarized by specific Tables containing workpiece material, input parameters or responses, and MOO methods used.

4.1. *Application area: electrical discharge machining*

The machining operations based upon electric discharge have considered the mainly admired topic in Entropy weights applications as 46% of articles belong to them. The electrical discharge machining (EDM) covers more than a few specific machining operations, including wire electrical discharge machining (WEDM), electric discharge diamond grinding (EDDG), electric discharge drilling (EDD), electric discharge

Table 1 – Decision matrix.

Exp. No.	MRR	Ra	Time
1	188	1.144	38
2	314	0.936	32
3	471	0.786	27
4	268	0.576	38
5	419	1.082	32
6	301	0.502	26
7	356	0.59	36
8	267	0.51	30
9	427	1.09	25
Maxi	**471**	**1.144**	**38**
Mini	**188**	**0.502**	**25**

Table 2 – Normalized decision matrix.

Exp. No.	MRR	Ra	Time
1	0.3992	0.4388	0.6579
2	0.6667	0.5363	0.7813
3	1.0000	0.6387	0.9259
4	0.5690	0.8715	0.6579
5	0.8896	0.4640	0.7813
6	0.6391	1.0000	0.9615
7	0.7558	0.8508	0.6944
8	0.5669	0.9843	0.8333
9	0.9066	0.4606	1.0000
SUM	6.3928	6.2450	7.2935

Table 3 – Probability of the normalized decision matrix.

Exp. No.	MRR	Ra	Time
1	0.0624	0.0703	0.0902
2	0.1043	0.0859	0.1071
3	0.1564	0.1023	0.1270
4	0.0890	0.1396	0.0902
5	0.1392	0.0743	0.1071
6	0.1000	0.1601	0.1318
7	0.1182	0.1362	0.0952
8	0.0887	0.1576	0.1143
9	0.1418	0.0737	0.1371

drilling (EDD), electro-chemical spark machining operations (ECSM).

4.1.1. *Electric discharge machining (EDM)*

EDM belongs to a non-conventional machining operation in which the tool has direct contact with the workpiece. At the same time, +ve-polarity specified to the workpiece and −ve-polarity assigned to the tool, which is generally copper or brass. The workpiece sinks into a dielectric fluid, and the electrode touched to the workpiece, so there is some metal erosion. The research studies which have the application of entropy weights in EDM operations are presented in Table 7. EDM has a share of 26% from all reviewed machining operations, as shown in Fig. 4. The multi-objective combination of MRR, tool wear rate, and Ra was studied by [71–78], and the higher entropy weight assignment is to MRR-48.2% and lower entropy weight to TWR-3.7% [65]. The gap and radial overcut were considered in addition to MRR, tool wear rate, and Ra by [66], and the maximum entropy weight assignment to Ra-25.8%. The MRR is considered as a response almost in all EDM MOO articles after by tool or electrode wear rate TWR and Ra. The maximum entropy weight assignment was to MRR (87%) when three or more than three responses were considered in the MOO [67] after by MRR-48.2% [65], and the minimum entropy weight assignment is to TWR-3.7% [65]. The GRA method was utilized a maximum number of times to get a composite score in EDM operations with entropy weight assignment after by TOPSIS and VIKOR methods. The Taguchi and RSM methods are frequently utilized for the design of experiments, as shown in Table 7.

4.1.2. *Wire electrical discharge machining (WEDM)*

It also belongs to a non-conventional machining operation invented in the 1960s for making the die from hardened steel. In this process, the tool electrode is of brass or copper wire, which is passing continuously through two spools, which works as holding and guiding the wire onto the workpiece; the process is carried out in the existence of dielectric fluid. It has a 12% contribution in the reviewed articles, as shown in Fig. 4. The WEDM responses were optimized simultaneously while using entropy weights. The responses include metal MRR, Ra, AE, G, kerf width, cutting rate, wire wear rate, and tooth width, as shown in Table 8. The Ra and MRR were optimized concurrently [82] in WEDM using brass wire and maximum entropy weight assignment to Ra-60%. The MRR is identified as a maximum considered response almost in all WEDM MOO studies except [83], followed by Ra and Kerf width. The

Table 4 – Entropy, divergence, and weights calculations.

	Exp. No.	MRR	Ra	Time
		$Pr_{ij}\log_e$	(Pr_{ij})	
Sr. No.	1	−0.1732	−0.1866	−0.2170
	2	−0.2357	−0.2108	−0.2393
	3	−0.2902	−0.2332	−0.2620
	4	−0.2153	−0.2748	−0.2170
	5	−0.2744	−0.1931	−0.2393
	6	−0.2302	−0.2933	−0.2671
	7	−0.2524	−0.2716	−0.2239
	8	−0.2148	−0.2912	−0.2479
	9	−0.2770	−0.1923	−0.2724
	Calculations			
I	$\sum_{i=1}^{n} Pr_{ij}\log_e(Pr_{ij})$	−2.1634	−2.1469	−2.1859
II	$Y = \frac{1}{\log_e(n)}$	0.4551	0.4551	0.4551
III	$En_j = -Y\sum_{i=1}^{n} Pr_{ij}\log_e(Pr_{ij})$	0.9846	0.9771	0.9948
IV	$Div_j = \lvert 1 - En_j \rvert$	0.0154	0.0229	0.0052
V	$\sum Div_j$	0.0424		
VI	Weight	0.3551	0.5273	0.1187
VII	Weight (%age)	35.51	52.73	11.87

Table 5 – Evolution of entropy method.

Author (s)	Entropy Development
Lahav and Gull [30]	Applied the maximum entropy technique to distances to clusters of galaxies.
Chen [31]	Evaluated utilizing fuzzy arithmetic operations taking an example of tactical missile selection.
Jianhui [32]	Suggested the grey relation entropy technique overcome the drawbacks of GRA.
Ruguo and Zhiwu [33]	Applied entropy weights in investment problems.
Yishu [34]	Selected water turbines by merging fuzzy assessment and entropy weights while eliminating subjective opinions.
Tran and Wagner [35]	Initiated the concept of fuzzy Entropy through a weight exponent on each fuzzy membership and applied to Butterfly and Iris data set.
Cunzhi [36]	Considered the investment value of stocks employing entropy weights.
Chi and Zhong [37]	Evaluated a large bank's performance by entropy weights.
Zhang et al. [38]	Used entropy weights in the multimedia problem.
Zhenghua and Wendong [39]	Applied entropy weights with AHP in logistics.
Xiao et al. [40]	Assigned EW to performance indicators to conquer the imperfection of precedent weight relative stability.
Gao et al., [41]	Applied EWs in urban ecological security appraisal.
Luo et al. [42]	Applied EWs to sustainable forestry development.
Huang [43]	Combined TOPSIS and EWs for the selection of an information system.
Shen et al., [44]	Evaluated the reliability of the CNC machine with EWs.
Liang et al. [45]	Combined EWs with extension theory to judge rock quality.
Li et al. [46]	Utilized TOPSIS and EWs to appraise safety in coal mines.
Feng et al. [47]	Used EWs to assess catastrophic failures in the power system.
Ouyang et al. [47]	Presented improved EWM with the addition of a comprehensive index of weights and applied to review power quality.
Zhang et al. [48]	Used improved EWM to estimate a model of eco-environmental susceptibility.
Ji et al. [49]	Conducted a case study of the Xiangxi River and integrated fuzzy EWs and MCDM to assess hydropower stations.
Delgado and Romero [50]	Carried out a study in Peru of a mining project and integrated grey and EWM to evaluate environmental variance investigation.
Lu et al. [51]	Utilized EWs to design a stand-alone energy system on Homer software.
Zhao et al. [52]	Evaluated the teaching system utilizing structure EWM.
Cui et al. [53]	EWM and set pair scrutiny to assess water source capability.
Zhang et al. [54]	Used intuitionistic fuzzy EWs in supply chain optimization.
Li et al. [55]	Utilized EWs with grey analysis to assess the health status of lithium-ion batteries.
Liang et al. [56]	Applied structure EWM for risk evaluation of gas pipe-line.
Zhu et al. [29]	Assessed the effectiveness of EWM in decision-making and referred to the water resource selection problem.

maximum entropy weight assignment was to MRR-70% when three or more than three responses were considered in MOO [84] after by MRR-25% [85], and the minimum entropy weight assignment is to Ra-10% [84]. The GRA method was utilized almost in all studies of WEDM to get composite scores except [86], which utilizes the MOORA method, as shown in Table 8. Pramanick et al. [87] also used GRA and RSM method to optimize multiple responses with entropy weights while designing experiments with the Taguchi method using brass wire and pure zirconium as workpiece material.

4.1.3. *Electric discharge diamond grinding (EDDG)*

A metal wheel bonded with a diamond in EDDG, and the grinding wheel impacts the workpiece that results in the abrasion of the workpiece, and at the same time, electrical spark causes the melting of the surface. The WEDM has only a 2% contribution in the reviewed articles as it has only one paper, as shown in Fig. 4. Shrivastava et al. [90] conducted experiments on composite material while optimizing material removal rate and wheel wear rate, refer to Table 9.

4.1.4. *Electric discharge drilling (EDD)*

The EDD also has only a 2% contribution in the reviewed articles as it has only one paper, refer to Fig. 4. Jayaraj et al. [91] optimized MRR and Ra while assigning entropy weights to the responses during electric discharge drilling of Inconel 718, as shown in Table 10.

4.1.5. *Electrochemical spark machining (ECSM)*

This hybrid operation consists of EDM and electro-chemical machining of non-conductive, hard, and brittle materials and mostly utilized for micromachining. The ECSM also has only a 2% contribution in the reviewed articles because of a single paper, refer to Fig. 4. Panda et al. [92] had utilized entropy weights assignment to responses, as shown in Table 11.

Table 6 – Application of cross-entropy in machining operations.

Author (s)	Year	Machining Operation	Methodology
Choi et al. [57]	1995	Diamond Turning	Cross-Entropy
Choi et al. [58]	1996	Diamond Turning	Minimum Cross-Entropy
Choi et al. [59]	1999	Turning	Cross-Entropy
Randall et al. [60]	2003	Milling	Normalized cross-entropy
Haber et al. [61]	2011	CNC-Drilling	Fuzzy Control, Cross-entropy
Beruvides et al. [62]	2016	Micro-Drilling	Cross-Entropy, Genetic algorithm
Fé-Perdomo et al. [63]	2018	Micro Milling	Cross-Entropy Method, Neural Networks, Fuzzy Inference Systems
Haber et al. [64]	2019	CNC-Machining	Cross-Entropy

4.1.6. *Green EDM*

The green EDM aims to enhance process efficiency and to diminish ecological impact and progress process efficiency. The green EDM has a 3% contribution in the reviewed articles because of one paper, as shown in Fig. 4. Jagdesh and Ray [93,94] optimized relative electrode wear rate, process energy, process time, dielectric consumption, and concentration of aerosol with TOPSIS and GRA methods, respectively, and assigned entropy weights, as shown in Table 12.

4.2. *Application area: laser-based machining operations*

The laser-based machining is a non-contact with the workpiece and without electrode type of machining operation. The metallic or non-metallic parts machined with the electric beam by utilizing thermal energy. The various machining operations based upon laser; such as laser beam machining (LBM), laser beam cutting (LBC), laser beam percussion drilling (LBPD), laser trepan turning (LTT), and the application of

Table 7 – EWM in "electrical discharge machining".

Author(s)/Year	Workpiece/Tool Material	Input Parameters	Responses/EW (%)	Other method (s)
Singh et al., 2010 [68]	WC-Co/spark	I, Ton, Toff, Df, Ws	MRR (33.29), WWR (33.42), Ra (33.27)	GRA, Taguchi, ANOVA
Sivasankar et al., 2012 [69]	ZrB_2/TI, GR, Nb, Ta, W, SS, Cu, Ag	I, Ton, Toff, Df, Ws	MRR (16.60), TWR (17.00), WWR (16.91), Ra (16.62), d (16.62), TA (16.65)	RA, ANOVA, E-GRA
Pardhan et al., 2012 [70]	AISI D2 Tool Steel/Cu	Ip, Pd, Dcy, Dv	MRR (33.3), TWR (33.3), G (33.4)	GRA, RSM, ANOVA
Pradhan, 2013 [71]	AISI D2 tool steel/Cu	Dc, Ton, Toff	MRR (33.3), TWR (33.3), Ra (33.4)	RSM, GRA
Majhi et al., 2013 [72]	–	Dc, Ton, Toff	MRR, TWR, Ra	RSM, GRA
Dadsena et al., 2013 [73]	85% ZRB2 + 15%	Ton, Toff	MRR (16.67), TWR (16.7), Ra (16.65), Rd (16.67), TA (16.66), G (16.67)	EG, GRA, ANOVA
Majhi et al., 2013 [74]	–	Ip, Ton, Toff	MRR, TWR, Ra	RSM, GRA
Routara et al., 2014 [66]	Al–12% SiC MMC/Cu	PkC, Ton, Fp	MRR (24.6), TWR (24.2), Ra (25.8), G (25.3)	RSM, TOPSIS, ANOVA
Sharma et al., 2014 [75]	AISI 329 stainless steel/Cu, brass	Ip, Pd, Toff, Dip	MRR, TWR, TA	Taguchi, GRA, ANOVA
Majhi et al., 2014 [76]	AISI D2 tool/Cu	DI, Ton, Toff	MRR, TWR, Ra	GRA, Taguchi
Bhuyan et al., 2015 [77]	Al 24% SiCP MMC/Cu	PkC, Ton, Fp	MRR (24.4), TWR (25.1), Ra (25.4), G (25.1)	OEC, FzI, ANOVA
Mahapatra et al., 2015 [67]	AISI H13/Cu	Dc, Ton, Toff, Sg	MRR (87), Ra (7), G (6)	Taguchi, ANOVA, GRA
Kasdekar et al., 2015 [78]	EN-353/Cu	Dc, Ton, Toff	MRR (45.9), TWR (21.8), Ra (32.3)	TOPSIS, SAW
Bhuyan et al., 2016 [79]	Al–18% SiCp MMC/Cu	Ton, PkC, Fp	MRR (24.5), TWR (24.5), G (25.1), Ra (25.8)	VIKOR, ANOVA
Mahapatra et al., 2019 [80]	Titanium alloy/Cu	V, Dc, Dcy, Ton	Ra (33.3), Rt (33.3), Rz (33.4)	Taguchi's (L_{27}), TOPSIS, VIKOR
Bhowmik et al., 2019 [65]	Ti-6Al-4 V alloy/Cu	DI, Pw, Ton/Toff, GV, LH	MRR (48.2), TWR (3.7), Ra (47.9)	SOW–WGRA
Tiwari et al., 2020 [81]	Al7075 alloy/Cu	Ton, Toff, I	Ra (33.2), Rz (33.3), PC (33.5)	ELECTRE–I, ELECTRE–II

Input: Ton-pulse duration on; Toff-pulse duration off; V-cutting speed; I-current; DI-dielectric current; PDff.-potential difference; Sg-spark gap; Dip-dielectric pressure; DI-dielectric current; Peg-process energy; Df-duty factor; v-voltage; Fp-flushing pressure; Pd-pulse duration; Dv-discharge voltage; Ip-pulse current; LH-lifting height; GV-gap voltage; Pw-pulse width; Dcy-duty cycle; PkC-peak current; Ws-wheel speed.

Table 8 – Application of EWM in "wire electrical discharge machining".

Author (s)/Year	Workpiece/Wire Material	Input Parameters	Response, EW (%)	Other method (s)
Jangra et al., 2012 [85]	WC/brass	PkC,Ton/off, Ws, Wt, Dfr, Sv	MRR (25), Ra (25), AE (25), G (25)	GRA, ANOVA
Bhuyan et al., 2014 [82]	Borosilicate glass/brass	Apv, Elct, WfV, W/pt	MRR (40), Ra (60)	GRA, Taguchi, RSM, ANOVA
Soni et al., 2015 [88]	Ti50Ni39Cu11/Brass	Ton, Toff, Sgv, Sf, Ws	MRR, Ra	GRA, RSM, (L_{25})
Varun and Venkaiah 2015 [84]	EN353/copper	Ton, Toff, PkC, Sv	MRR (70), Ra (10), Krfw (20)	GRA, GA, ANOVA
Barman et al., 2015 [83]	WC-Co composite/brass	PkC, Ton, Toff, WfR	Ra (49.81), CR (50.19)	GRA, Taguchi,
Mohapatra et al., 2017 [89]	Titanium/brass	Ton, Toff, Wt	MRR, Krfw, WWR, Tw	GRA, GRD
Muniappan et al., 2018 [86]	AZ91 magnesium alloy/coated brass	Ton, Toff, I, Gpv, Ws, Wt	V, Krfw	MOORA, Taguchi

Input: PkC-peak current; Ws-wire speed; Wt-wire tension; Dfr-dielectric flow rate, Sv-servo voltage, Apv-applied voltage; Elct-electrolyte concentration; WfV-wire feed velocity; W/pt-workpiece thickness; Ton-pulse on time; Toff-pulse off time; Sgv-spark gap voltage, Sf-service feed; WfR-wire feed ratio; I-current; Gpv-gap voltage.

Table 9 – Application of EWM in "electric discharge diamond grinding".

Author (s)/Year	Workpiece Material	Input Parameters	Responses, EW (%)	Other method (s)
Shrivastava et al., 2013 [90]	Copper-Iron-Graphite MMC	PkC, Ton/off, Grit No.	MRR (46), WWR (54)	ANN, GA, GRA, EWM

Input: PkC-peak current; Ton-pulse on time; Toff-pulse off time.

Table 10 – Application of EWM in "electric discharge drilling".

Author (s)/Year	Workpiece/Tool Material	Input Parameters	Responses, EW (%)	Other method (s)
Jayaraj et al., 2019 [91]	Inconel 718/Cu electrode	PkC, Ton, Toff	MRR (50), Ra (50)	RSM, TOPSIS

Input: PkC-peak current; Ton-pulse-on time; Toff-pulse-off time.

Table 11 – Application of EWM in "electrochemical spark machining".

Author (s)/Year	Workpiece Material	Input Parameters	Responses, EW (%)	Other method (s)
Panda et al., 2012 [92]	Silicon nitride	Sv, Son, Ec	MRR (50.5), Ra (49.5)	GRA, FEM

Input:Son-spark on-time; Ec-electrolyte; Sv-servo voltage; Ra-surface roughness.

Table 12 – Application of EWM in "green EDM".

Author (s)/Year	Workpiece/Tool Material	Input Parameters	Responses, EW (%)	Other method (s)
Jagdesh and Ray, 2014 [93]	Ti-6Al-4 V/tool steel	PkC, Pd, DiL, Fp	REWR (17.6), PE (17.2), CA (22.3), DC (6.5)	TOPSIS
Jagdesh and Ray, 2015 [94]	Ti-6Al-4 V/tool steel	PkC, Pd, DiL, Fp	PT (17.61), REWR (17.22), PE (36.37), CA (22.3), DC (6.5)	GRA

Input: PkC-peak current; Pd-pulse duration; DiL-dielectric level; Fp-flushing pressure.

Table 13 – Application of EWM in "laser beam-based machining".

Author (s)/Year	Operation/Process	Work Piece Material	Input Parameters	Responses, EW (%)	Other method (s)
Rao et al., 2009 [24]	LBM	SUPERNI718	Op, Pw, Pf, V	K_w (33.33), K_t (33.33), K_d (33.33)	GRA, Taguchi
Sharma and Yadava, 2013 [95]		Al-alloy	Arad, Op, Pw, Pf, V	Ra (49.9), Kd (50.1)	GRA, Taguchi
Goyal and Dubey, 2015 [96]		Ti-6Al-4V	H-T, C (top), C (bottom)	Taper, Circularity	GRA, ANN
Belinato et al., 2019 [97]		AISI 314S	Lf, V, Lp, Pint	MRR, Ra, Rq, Rz	RSM, PCA, GPE
Sivaprasad and Haq, 2019 [98]		Alloy-X	P, Pf, Pw, Gprss	MRR (39.72), Dt (12.09), Db (15.96), Taper (8.60), $C_{entry}E$ (12.25), $C_{exit}E$ (11.35)	MCDM, RSM
Sharma and Yadava, 2011 [99]	LBC	SUPERNI 718	Op, Pw, Pf, V	R_a (49.90), Kd (50.10)	GRA, Taguchi
Sharma and Yadava, 2012 [100]		Al-alloy	Op, Pw, Pf, V	Ra (50.10), Kd (49.90)	GRA, ANOVA
Alam and Haque, 2013 [101]	LTT	Ti alloys sheet	Pw, Pd, Pf, AvgP, V	NHT (33), $NCIR_{entry}$ (33), $NCIR_{exit}$ (34)	GRA, ANN, RSM, Taguchi, GA
Mishra and Yadava, 2013 [102]	LBPD	Aluminum sheet	AvgP, Pw, Pf, Nsf D	MRR (50.01), Ra (49.99)	GRA, ANN

Input: Op-oxygen pressure; Pw-pulse width; Pf-pulse frequency; V-cutting speed; Arad-arc radius; H-T-hole taper; C (top)-circularity at top; C (bottom)-circularity at bottom; Lf-laser frequency; Lp-laser power; Pint-Pulse intensity; P-power; Gprss-gas pressure; Pd-pulse duration; AvgP-average pressure; Nsf D-nozzle standoff distance.

entropy weights in these operations are shown in Table 13. The laser-based machining operations have a 14%share in all reviewed articles.

Rao et al. [24] evaluated entropy weights for kerf width, kerf thickness, and top kerf deviation and concurrently optimized by GRA for LBM. The surface roughness responses and MRR were optimized with RSM and PCA while assigning entropy weights in LBM [97]. In other research studies of LBM, the GRA method was utilized to optimize responses simultaneously, as shown in Table 13. The LBC operation was optimized, considering top kerf deviation and Ra with the GRA method [99,100]. Alam and Haque [101] computed entropy weights for different responses of LTT operation and optimized the responses with GRA and ANN methods. Mishra et al. [102] optimized MRR and Ra in LBPD operation with the GRA technique while assigning entropy weights.

4.2.1. *Ultrasonic machining (USM)*

In this operation, metal removal by the vibration of the tool beside the work part and abrasive slurry. The ultrasonic machining has a 2%share in all reviewed articles. Dhuria et al. [103] utilized USM to machine Ti-6Al-4V while optimizing MRR and TWR with GRA and ANN, as shown in Table 14.

4.3. *Application area: CNC-based machining operations*

The machining operations based upon computer numerical control (CNC) are included in this section. CNC-based machining operations contribute 11% of the available articles, as shown in Fig. 4.

4.3.1. *CNC turning*

In this operation, the workpiece revolves while the cutting tool travels corresponding to the workpiece axis. It can be performed on the external and internal surface of the workpiece either manually or automatically on a lathe machine. The manual turning operation performed on a conventional lathe machine, which often requires nonstop control by the operator, or it can also be performed automatically without the command of the operator on the CNC machine. The CNC turning has an 8% share in all reviewed articles, as shown in Fig. 4. Park et al. [104–106], optimized specific energy consumption and energy efficiency with different methods while assigning entropy weights, and Kumar et al. [3], also optimized energy responses, refer to Table 15.

4.3.2. *CNC milling*

In simple milling, the workpiece is held stationary, and the tool is in motion (anticlockwise) having multi-point cutting edges. The CNC milling carried out with the use of a computerized based machine; if the end mill cutter is utilized, then it is called CNC End Milling. The CNC turning has a 3% share in all reviewed articles, refer to Fig. 4. Moshatet al. [108]; Ren et al. [109] both used the GRA method to optimize CNC milling responses with entropy weights, as shown in Table 16.

Table 14 – Application of EWM in "ultrasonic machining".

Author (s)/Year	Workpiece Material	Tool Material	Input Parameters	Responses, EW (%)	Other Method (s)
Dhuria et al., 2017 [103]	Ti–6Al–4V	Stainless steel, High-carbon steel, Ti	Slurry & tool type, power rating, grit size, tool & workpiece treatment	MRR (49.98), TWR (50.02)	GRA, ANN, Taguchi

Table 15 – Application of EWM in "CNC turning".

Author (s)/Year	Work Piece/Tool Material	Input Parameters	Responses, EW (%)	Other method (s)
Singaravel et al., 2016 [107]	EN25 steel/carbide	V, f, d, NR	Ra (33.32), MH (33.22), MRR (33.45)	MOORA
Park et al., 2016 [106]	AISI 4140/CBN	f, Ss, d	SCE (70), EE (30)	FEM, ANOVA
Park et al., 2016 [106]	AISI 4140 steel/carbide	V, f, d, NR, α, β	SCE (72), EE (28)	TOPSIS, FEM, ANOVA
Park et al., 2016 [106]	AISI 4140 steel/CBN	V, f, d, NR, α, β	SCE (70), EE (30)	TOPSIS, MOPSO
Kumar et al., 2017 [3]	EN 353/carbide	V, f, d, NR	APCM (1.16), PF (0.09), AECM (7.78), EE (12.94), MRR (26.27), Ra (51.27)	TOPSIS, AHP, Taguchi

Input: V-cutting speed; f-feed; d-depth of cut; NR-nose radius; Ss-spindle speed; α-rake angle; β-relief angle.

Table 16 – Application of EWM in "CNC-Milling machining".

Author (s)/Year	Operation	Work Piece/Tool Material	Input Parameters	Responses, EW (%)	Other method (s)
Moshat et al., 2010 [108]	CNC Milling	Aluminum/carbide	Ss, f, d	Ra (50), MRR (50)	GRA, Taguchi
Ren et al., 2016 [109]	CNC Milling	Ti-alloy/end mill	Rrk, Prra, Ha	SRb (28.8), SRs (29.2), RSb (23.5), RSs(18.3)	GRA, Taguchi, AHP

Input: Ss-spindle speed; f-feed; d-depth of cut; Rrk-radial rake angle; Prra-primary radial relief angle; Ha-helix angle.

4.4. *Application area: conventional machining operations*

4.4.1. *Conventional turning*

Turning operation is the most fundamental and aged machining operation in the manufacturing units; the workpiece is revolving while the cutting tool travels corresponding to the job. It is called duplex turning when the cutting tool removing material on both sides of the workpiece. When the workpiece held at the vertical position, it is called vertical turning, which is suitable for large and heavy components. The conventional turning has 12%, duplex turning 2%, and vertical turning 3%, share in all reviewed articles, as shown in Fig. 4. There are eleven research studies in conventional turning with entropy weights; eight studies belong to turning operations, two studies belong to vertical turning, and one to duplex turning. In these studies, different materials were taken to optimize diverse responses. Ra considered response with a maximum entropy weight of 34.1% [110], and the minimum weight assigned was 19.1% [109]. The WASPAS and GRA methods utilized to get a composite score in turning operations, but GPE is used in vertical turning, refer to Table 17.

4.4.2. *Conventional drilling*

In conventional drilling, a drill bit having a multi-point cutting tool is rotated about clockwise and pushed in opposition to the workpiece to make a hole in the solid workpiece. The conventional drilling has a 5% share in all reviewed articles, shown in Fig. 4. The VIKOR method utilized by Shaik et al. [121], and Kakaravada et al. [122], to optimize multiple responses, while fuzzy logic used by Haber et al. [123], with entropy weight assignment, as shown in Table 18.

4.4.3. *Conventional milling*

In this operation, the cutting tool has multi-point cutting edges. It rotates about its axis; the workpiece is set aside motionless and moved at a right angle to its axis to cut the material. The CNC turning has a 6% share in all reviewed articles, refer to Fig. 4. The VMD, GRA, and TOPSIS methods are utilized to optimize multiple responses in a conventional milling operation, as shown in Table 19.

5. Other categorization proposal

The following features are used to describe the organization of EWM publications in machining operations: (1) application of EWM in different machining operations, (2) multi-objective optimization methods used with entropy weights in machining operations, (3) application of entropy weights by citation index and publication year, (4) entropy weights applications in other fields.

5.1. *Use of entropy weights in different machining operations*

The use of entropy weights in machining operations divided into two groups conventional and non-conventional, as shown in Fig. 2. The conventional machining has a 28% share, and non-conventional machining has a 78% share of the

Table 17 – Application of EWM in "conventional turning".

Author (s)/Year	Operation	Work Piece/Tool Material	Input Parameters	Responses, EW (%)	Other method (s)
Rajesh et al., 2014 [110]	Turning	Al MMC/VCGX	V, f, d, NR	Ra (34.1), FW (32.9), PC (32.9)	GRA, Taguchi,
Rajesh et al., 2014 [112]		AISI 4140/CVD coated	N, f, d	Ra, MRR, PC	Taguchi, ANOVA, ANN, GA
Stryczek and Pytlak, 2014 [113]		18CrMo4 Steel/CBN	V, f, d, LCD, UPC, T, RCf	Ra, Rz, Rmax	PSO
Li et al., 2016 [114]		Al-Si alloy/CBN, PCD, Ceramics	Tool material properties	D (07.1), YM (12.1), H (18.3), FT (11.1), TS (10.2), TC (25.1), TEC (16.1)	AHP
Rehman et al., 2017 [115]		Inconel 718/carbide	T, Ss, f	MRR (31.27), PC (19.71), Ra (17.48), ThF (13.29), f (20.94), V (12.28)	WASPAS, ABAQUS Software
Suresh et al., 2017 [111]		Hardened AISI D3/CVD coated	S, CF, V, f, d	Ra (19.1), MRR (30.8), T (01.7), SEC (18.9), FW (29.5)	WASPAS, DENG'S, ANOVA
Suresh et al., 2017 [116]		Hardened AISI D3 steel/CVD coated	S, CF, V, f, d	Ra, MRR, ITem, SEC, FW	WASPAS Method, ANOVA
Sterpin et al., 2019 [117]		X20Cr13/carbide	V, f, d, CC	Ra (24.9), Rz (24.9), TL(25.1), MRR (25.1)	GRA, Taguchi
Kumar et al., 2019 [118]	Duplex turning	Ni-718 alloy/carbide	Cv, f, d	PFc (34.81), SF (32.77), Ra (32.29)	GRA, Taguchi
Rocha et al., 2015 [119]	Vertical turning	–	f, N	TL (48.76), Prod. (3.57), C (47.65)	GPE
Rocha et al., 2015 [120]	Vertical turning	Martensitic Gray C.I.	f, N	TL (49.76), Prod. (0.0), C(50.24)	GPE

Input: V-cutting speed; f-feed; d-depth of cut; NR-nose radius; N-speed; LCD-length of cutting distance; UPC-unit production cost; T-temperature; RCf-resultant cutting force; Ss-spindle speed; CF-cutting force; S-insert style; Cv-cutting velocity; CC-cooling condition; f-feed; N-rotation.

collected articles on entropy weights. Further, entropy weight applications are divided into other groups, as shown in Fig. 5. It shows the contribution of the different machining operations. The electrical discharge based machining has the maximum share of 46%, followed by turning-based machining 17%, laser-based machining 14%, CNC-based machining 11%, milling-based machining 6%, drilling-based machining 5% and ultrasonic machining 2%.

5.2. *Multi-objective optimization (MOO) methods used with entropy weights*

In MOO problems, different methods were used to get composite scores. Various methods utilized with an application of EWM are shown in Fig. 6. The GRA has a share of 50% and used a maximum number of times out of 14 methods. The TOPSIS method has a share of 11%, followed by ANN 8%, VIKOR 6%, WASPAS, and AHP 4% each, fuzzy logic, and MOORA 3% each. The VMD, PSO, SAW, ELECTURE and PCA have only a 1% share.

5.3. *Application of entropy weights by publication type and year*

Fig. 7 shows valuable information regarding publication types in various resources. The collected review articles are divided into five categories SCI journals, Scopus journals, non-SCI & Scopus journals, conference articles, and book chapters. Out of the reviewed 65 articles, maximum articles have been published in SCI journals (26), followed by Scopus journals (20) and in non-SCI & Scopus journals (13). Four articles published in different conferences and 2 in book chapters.

Fig. 8 provides valuable information concerning the articles published year-wise. Since 2009, there was a substantial expansion in articles published on entropy weights applications in machining operations. The year 2015 and 2019 tops the list with a 15% share, out of the total article published since 2009. The year 2009 is assumed as a starting year of the reviewing process, which only contributes 1% of articles. The other year-wise contributions can be seen from Fig. 8. The year 2020 only shows a 2% contribution because the publication process is still going on during the paper writing and publication procedure.

5.4. *Entropy weights applications in other fields*

The EWM other than machining operations were also applied in many fields of industrial engineering, human resource, and management. Some of the areas of applications of EWM are presented in Table 20 for the knowledge of future researchers.

Kumar et al. [3], compared the concert of various responses in MOO while assigning equal weights, entropy weights, and AHP weights. The results reveal that the AHP performed better. Ren et al. [109], also used AHP and EWM in CNC milling operation refer to Table 15.

6. Concluding remarks

This paper reviewed entropy weights applications in machining operations to categorize and construe the

Table 18 – Application of EWM in "conventional drilling".

Author (s)/Year	Work Piece/Tool Material	Input Parameters	Responses	Other method (s)
Haber et al., 2010 [123]	CI GGG40/HSS	f, Ss, Dpt	ITAE, ISTSE, Ovt%	Fzl
Shaik et al., 2018 [121]	EN-24 steel/HSS	Ss, Dfr	Ra, ThF	VIKOR, Taguchi, ANOVA
Kakaravada et al., 2018 [122]	A356 alloy/carbide	Drd, Ss, Ref	MRR, Df, Ra	VIKOR

Input: f-feed; Ss-spindle speed; Dpt-depth; Dfr-dielectric flow rate; Drd-dill diameter; Ref-reinforcement.

Table 19 – Application of EWM in "conventional milling".

Author (s)/Year	Operation	Work Piece/Tool Material	Input Parameters	Responses	Other method (s)
Liu et al., 2019 [124]	Milling	Al-alloy/UA100-R3	Rd, Ad, f, N	Chatter Detection	VMD
Sreenivasulu et al., [125]	Milling	GFRP/K10 Carbide	V, f, d	Ra (50.06), ThF (49.93)	GRA, Taguchi
Li et al., 2019 [55]	Milling	Titanium alloy/HSS	Ss, f/T,d	–	GRA, Meta-Learning,
Sen et al., 2019 [126]	Milling	Inconel 690/uncoated carbide	V, f, d, Q, θ	Ra, CF, CT, TW	TOPSIS, GEP, NSGA-II ANOVA

Input: Ss-spindle speed; d-depth of cut; Rd-radial depth; Ad-axial depth; f-feed; N-rotation speed; V-cutting speed; Q-MQL flow rate; MQL-minimum quantity lubrication; θ-nozzle inclination angle; f/T-feed per tooth.

Table 20 – Other fields of applications of EWM.

S. No.	EWM Applications Area	Author (s)/Year
1	Corporate's Performance	Chi and Zhong, 2002 [37]
2	Business and Marketing Management	Zhang et al., 2007; Yang and Tang, 2008 [127,128]
3	Chemical Engineering	Jian et al., 2008; Pan et al., 2015 [129,130]
4	Coal Mines	Li et al., 2011, Liang et al., 2019 [46,56]
5	Construction Work	Guo, 2017; Lam et al., 2019 [131,132]
6	Cyber Security	Hamid et al., 2016; Parveen et al., 2020 [133,134]
7	Energy Management	Lu et al., 2017; Mohsen et al., 2017 [51,135]
8	Forecasting	Hua, 2003; Yan and Shang, 2019 [136,137]
9	Human Resource management	Krylovas et al., 2017; Elsayed et al., 2017 [138,139]
10	Mining Project	Delgado and Romero, 2016; Delgado, 2017 [50,140]
11	Power Quality	Ouyang et al., 2013; Sacasqui et al., 2018 [47,141]
12	Risk Assessment	Dong et al., 2010; Ji et al., 2015 [49,142]
13	Supply Chain Management	Gong et al., 2012; Kiani et al., 2016 [143,144]
14	Water Resource Management	Ding et al., 2019; Lu et al., 2019 [145,146]
15	Pharmaceutical Industry	Suifan et al., 2019; Zhao and Du, 2017 [147,148]

continuing and emerging issues. The review categorized 65 scholarly articles from 26 SCI journals, 20 Scopus journals, 13 non-SCI & Scopus journals, four conferences, and two book chapters since the year 2009. The papers in the EWM applications are further inferred based on the implementation of EWM in different machining operations, MOO methods used, by citation index, publication year, and applications in other fields. For future researchers, the example of the MOO problem was solved in Excel (MS office) with calculations of all the steps. The calculation of entropy weights on Excel is very effortless, logical, and has higher computational simplicity. This approach is very favorable for researchers/engineers/managers, even for a programmer of websites or developer of online calculator/software working on EWM growth.

Since the inception of EWM, there are several advances in methodology and is applied in different fields of engineering and management. The fuzzy entropy method was used to obtain entropy weights in a vague environment. The cross-entropy method has been developed and evaluated in machining processes. The modified multi-objective cross-entropy method was successfully applied based on a new approach for addressing constraints. The EWM combined with subjective influences such as the AHP method. The grey entropy technique was utilized to improve GRA. The intuitionistic fuzzy entropy weights are progressed along with extension theory, and the enhanced EWM developed with comprehensive index weights. Still, the research is in progress for the expansion of the method.

The EWM applications in non-conventional machining operations are 72% and 28% in conventional machining. All the machining operations are further divided into 18 processes, and 26% of papers belong to EDM operation followed by WEDM and conventional turning 12%. The electric discharge-based machining group contributed 46%, followed by turning-based machining 17%, and laser-based machining 14%. Fourteen MOO methods are identified in different machining operations and the GRA has a maximum contribution of 50%, followed by TOPSIS 11%, and ANN 8%. The starting year of the review process only contributed 2% articles, and the maximum number belongs to the year 2015 and

2019, followed by the year 2016, 14%. Indian authors contributed 82% of papers, followed by China 6%. Only six countries contributed papers related to EWM application in machining operations.

The material used in experiments, input variables, responses, and entropy weights assigned in different machining operations will help for the future design of experiments. Still, there is more attention to be paid on the application of entropy weights as the research completed on EWM in machining is too low comparatively. Still, there are many machining operations in which EWM is not used, and many processes have only one paper, such as ECSM, EDD, EDDG, and ultrasonic machining. The EWM has applications in various other fields, as presented in Table 20. The insights recognized by EWM in machining operations will help channel future research efforts of researchers and practitioners.

Further, the entropy weights can be merged with subjective influences and can be utilized in MOO problems. The weights can be assigned to the output parameters with EWM, equal, and subjective weights, and the attained results can be compared for better achievement of the objectives. Still, only a few studies were available of MOO in which results were compared with different weight assignment. Besides, it endeavors to furnish the user/researcher with adaptability to apply EWM in MOO problems for the betterment of the outcome. The review of EWM will help to establish novel directions in MOO of machining operations.

Declaration of Competing Interest

There is no conflict of interest.

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